0587888 BW1116

CHARLES SCHWAB: Schwab introduces Analytics Fund; utilizes quantitative techniques to seek above-market returns

May 21, 1996

Ticker Symbol: SCH
Byline: Business Editors
Dateline: SAN FRANCISCO
Time: 06:21 PT
Word Count: 737

SAN FRANCISCO--(BUSINESS WIRE)--May 21, 1996--Charles Schwab & Co. Inc. introduced today a new proprietary equity mutual fund, the Schwab Analytics Fund(TM), which will utilize quantitative techniques, proprietary software models and real-time databases to structure and manage a portfolio of stocks with attributes historically associated with returns above that of the S&P 500(R) Index.

Managed by Charles Schwab Investment Management Inc., the Schwab Analytics Fund is part of the growing SchwabFunds Family(R), which now includes 24 proprietary funds with over $35 billion in assets. The fund will invest primarily in stocks of medium- and large-capitalization U.S. companies -- that is, those with market capitalization above $500 million.

Selection Criteria: Valuation, Analysts, Insider Selling

Focusing on a universe of approximately 1,300 such companies, the Schwab Analytics Fund will apply three major sets of criteria to rank companies for performance potential, as an initial step in maintaining a portfolio of some 50 to 100 stocks with characteristics historically associated with high performance.

The criteria are valuation factors, such as stock price momentum and price-earnings ratio; the reports (for example, earnings or ratings changes) of securities analysts whose recommendations historically have correlated most closely with a stock's actual performance (termed "smart analysts"), and unusual selling patterns by major company executives and shareholders (which will exclude a company from the performance rankings).

After the fund model ranks companies according to high return potential, the fund managers will select stocks to seek industry diversification similar to that of the S&P 500 in order to manage risk.

"The Schwab Analytics Fund employs no mysterious 'black box' techniques but rather an open 'lucite box' approach with a fund manager using models that analyze securities from three vantage points -- valuation, the 'smart analysts' and insider selling," said William Klipp, president and COO, Charles Schwab Investment Management Inc. "It's an approach that many of our investors would take if they had the time and resources."

The Schwab Analytics Fund brings quantitative analysis -- a widely used institutional investment approach -- to the retail investor. The fund aims to address investor interest in disciplined, analytical methods of mutual fund investing designed to achieve better-than-market long-term returns without significantly

greater risk. It is not guaranteed that the fund will reach its goals. The fund fits in the large company domestic stock asset allocation category, and may be ideal for IRAs, college savings or other long-term investment objectives.

Evidence of Funds Family Strategy

"Our strategy for the SchwabFunds Family(R) is to identify market segments where we can add value for our customers and introduce funds with innovative features specifically designed to address emerging investor needs," said Michelle Swenson, SVP Mutual Fund Development. "The Schwab Analytics Fund -- with its disciplined, yet readily understood approach to 'quant' investment -- is additional strong evidence of this strategy."

The SchwabFunds Family(R) complements other fund opportunities available through Schwab such as the Mutual Fund OneSource(R) service, which offers access without brokerage fees to 548 mutual funds from 70 well-known fund families, and the Mutal Fund Marketplace(R), a one-stop service for investment in 1,100 mutual funds offered by 160 fund families.

During the Schwab Analytics Fund's initial subscription period, from May 21 through June 28, the fund share price will be $[illegible]. After this period, the share price will fluctuate. The subscription period may be extended.

No loads or transaction fees are required to invest in the Schwab Analytics Fund. Charles Schwab & Co. and the Investment Manager guarantee the fund's operating expenses will not exceed 0.75 percent through July 1, 1997. The minimum initial investment is $1,000 ($500 for Individual Retirement Accounts). Investors can add to their original fund investment in amounts of $100 or more.

The prospectus containing more complete information including management fees, charges and expenses is available from Schwab. Please read it carefully before investing.

Note to Editors: Charles Schwab & Co. Inc. is one of the largest financial services firms in the nation, serving over 3.6 million active investor accounts with over $208 billion in customer assets through a nationwide network of 223 offices. Member SIPC/NYSE.

The Standard & Poor's 500 Index includes common stock of 500 publicly traded U.S. companies. Investments cannot be made in indexes which are unmanaged and do not incur transaction fees or other related expenses.

CONTACT: Charles Schwab & Co. Inc., San Francisco
Tom Taggart, 415/627-8947
or
Ogilvy Adams & Rinehart, New York
William Haynes, 212/880-5311

KEYWORD: CALIFORNIA

INDUSTRY KEYWORD: BANKING COMPUTERS/ELECTRONICS COMED PRODUCT

01583992 02-34981
Market reactions to messages from **brokerage ratings systems**
Ho, Michael J; Harris, Robert S
Financial Analysts Journal v54n1 PP: 49-57 Jan/Feb 1998 CODEN: FIAJA4
ISSN: 0015-198X JRNL CODE: FIA
DOC TYPE: Journal article LANGUAGE: English LENGTH: 9 Pages
SPECIAL FEATURE: Charts Equations References
WORD COUNT: 4412

ABSTRACT: One dimension of the strategies investment houses use to present investment advice is the number of categories in their rating system. A study examined 3-, 4-, and 5-level systems and found that in all rating systems, upgrades outnumber downgrades. Price reactions are more pronounced to multiple-level than to single-level recommendation changes and to recommendation upgrades to the highest rating category. These price reactions confirm that the market gleans new information from analysts' research but suggest that investors, at least partially, recognize analysts' tendency toward optimism and thus react strongly to downgrades. The price effects also show that adding more rating categories is not simply a way to portion out information in smaller bits. Some of the largest price reactions are to changes between the top 2 categories in a 5-level system, even though the descriptions of the categories would not signal a portfolio action. The results are consistent with the view that firms try to avoid issuing harshly worded recommendations, which might compromise revenue generation. A system with more rating categories provides for less-direct statements of bad news.

TEXT: Headnote:

One dimension of the strategies investment houses use to present investment advice is the number of categories in their rating systems. We studied three-, four-, and five-level systems and found that in all rating systems, upgrades outnumber downgrades. Price reactions are more pronounced to multiple-level than to single-level recommendation changes and to recommendation upgrades to the highest rating category. These price reactions confirm that the market gleans new information from analysts' research but suggest that investors, at least partially, recognize analysts' tendency toward optimism and thus react more strongly to downgrades. The price effects also show that adding more rating categories is not simply a way to portion out information in smaller bits. Some of the largest price reactions are to changes between the top two categories in a five-level system, even though the descriptions of the categories would not signal a portfolio action. Our results are consistent with the view that firms try to avoid issuing harshly worded recommendations, which might compromise revenue generation. A system with more rating categories provides for lessdirect statements of bad news.

"What's in a name? That which we call a rose by any other name would smell as sweet."

Shakespeare, Romeo and Juliet, Act 2, Scene 2

One of the major sources of investment information is brokerage firms' research. Highly trained equity analysts provide their customers with detailed information, including specific investment recommendations. Equity

research, however, historically accounts for no direct revenues for brokerage firms and investment banks, although it does generate business through indirect channels, such as trading commissions and underwriting fees. Structuring research information thus poses a substantial challenge for any research director. How should research be presented to convey information and still recognize the ways the firm is compensated? From the investor's perspective, the challenge is how to interpret the investment advice given in the research report.

Firms have adopted a number of strategies for presenting research advice. In this article, we look at one dimension of those strategies, the number of categories used in a firm's rating system. Some firms adopt a triage approach (buy, neutral, and sell), whereas others have finer partitions. A simplistic interpretation would be that more rating categories are just a means of conveying information in smaller units.

We find that all rating systems exhibit a preponderance of upgrades relative to downgrades. The evidence further suggests that adding rating categories gives analysts "wiggle room," which they use to avoid explicitly stating negative recommendations. Such a rosy bent likely reflects the unfavorable revenue effects of negative ratings. Prices react significantly to rating changes, and reactions to downgrades typically are larger than those to upgrades. Results also show more-pronounced price reactions to multiple-(versus single-) level recommendation changes and to recommendation upgrades to the highest rating category. These price reactions confirm that analysts' research provides the market with new information, but they also suggest that investors, at least partially, recognize analysts' tendency to optimism and thus react more strongly to downgrades. The price effects also show that adding more rating categories is not simply a way to portion out information in smaller bits. For a one-level recommendation change, price reactions are at least as large in a five-level system as in a three-level system. Some of the largest price reactions are to changes between the top two categories in a five-level system, even though a reading of the category wordings would not literally signal a portfolio action.

These patterns suggest that the information exchange between analysts and investors involves subtle interpretations that go well beyond the actual wording of rating categories. Our results are consistent with the view that firms try to avoid issuing harshly worded recommendations (e.g., sell). Such blunt, negative statements may compromise revenue generation, and a system with more rating categories provides for less-direct statements of bad news.

Ratings and Incentives

Brokerage firms issuing research reports can generally anticipate economic rewards through two routes. The first, and most direct, is via trading commissions. These come from clients who channel business to the firm in exchange for research information and/or come from commissions on surges in trading volume accompanying a specific recommendation change. The second route for full-service investment banks is through fees from companies, including underwriting fees from financings. Research capability may be a key factor in a company's choice of an investment banker. Specific negative research views on a company, however, may compromise the firm's chances to work for a client company. As a result, many firms issuing research reports have both investor and subject-company constituencies for revenue flows linked to the research function.

Such tugs on incentives have naturally led to considerable skepticism about the objectivity of research analysts. To quote one well-known observer of research output, "brokerage research departments rarely offer 'sell' advice. Because brokers too easily begin to believe their own sales pitches, this may lead them to become permanently bullish on the market" (Hulbert 1993). Such optimism tied to brokerage commissions may be further reinforced by pressures from subject companies themselves. Certainly,

public perception of such company pressure is widespread.

The pressure to av[redacted] issuing unfavorable report[redacted] is intensifying as investment banking comes to account for a greater portion of many firms' revenues. The conflict lies in the dramatic increase in the relative contribution of investment banking fees and revenues to the senior-analyst compensation structure.

Business Week, November 4,1996
It's a fact of life among Wall Street securities analysts: Bash a company and brace for the deep freeze.... The retribution for negative reports takes many forms. Analysts are excluded from meetings, outings and conference calls with top company executives. Analysts' firms are put in the "penalty box"-that is, bounced from trading and underwriting deals for a period of time. Company executives publicly belittle the naysayers. In some cases, offended companies try to get them fired.

Wall Street Journal, July 19,1995

In this setting, brokerage firms have adopted a number of tacks to stock-rating categories. Some adopt a basic three-level approach, but more frequently, firms create finer shades of descriptionup to five levels. One reason for increasing the number of rating categories might be the ability to convey finer bits of information. If more categories simply allow an analyst to communicate smaller amounts of private information, the market reaction to a single-rating change from a five-level system should be less than from a system with fewer rating levels. More categories may also provide more flexibility to individual analysts within the firm. Our discussion of incentives highlights the potential for another purpose: More categories may provide an opportunity to sugarcoat bad news and/or to send more-subtle signals. For instance, in a five-level system, a recommendation downgrade to an "underperform" may be substituted for the harsher change to the bottom category of "sell."

Examination of brokerage houses' descriptions of rating categories provides further indication of attempts to manage investor sentiment. Although many firms use relatively straightforward labeling (e.g., a five-level system of "buy, attractive, neutral, unattractive, sell"), others use more nuance. Some houses avoid the word "sell" altogether, using "underperform" as the most negative rating. Even more suggestive of incentive effects is one brokerage firm's bottom rating of "swap-this issue should be used as a source of funds to purchase other, more attractive issues."1

Although many studies have addressed analysts' recommendations (see, e.g., Stickel 1995 and the references therein) and share-price reactions, they have produced little or no evidence on the effects of the rating systems used. Our study focuses specifically on potential differences in market reactions to signals from three-, four-, and five-level rating systems. By gathering data with the rating systems in mind, we were also able to examine differences between multilevel and single-level recommendation changes more precisely than is possible with some widely used secondary data sources.2

Sample and Methods

We studied 4,436 recommendation changes drawn from Thomson Financial Services' Investext database, a broad collection of reports by investment banks and brokerage firms. Investext provides the full text of company research reports generated by more than 1,000 financial analysts from more than 300 leading investment banks (foreign and domestic) and credit-rating agencies. To develop a comprehensive data set, we electronically screened all reports from January 1989 through July 1, 1992, and identified those that mentioned a change in recommendation. We then scanned the full text of the identified reports to confirm that a recommendation change did occur and to gather the names of the company and the issuing institution (and analyst), the report publication date, and the type of rating system used.

To cross-check our filters, we provided three independent industry practitioners with a random sample of 10 electronically selected research reports. In all cases their identifications of the recommendation change and the new rating level were consistent with those generated by our automated procedure.

We then matched the observations with the CRSP daily return files (covering NYSE, Amex, and OTC firms) and Compustat tapes to obtain sharereturn data for the 241-day period centered on the publication date of the analyst report. To avoid confounding effects of multiple reports on the same company in a relatively short time frame, we excluded all clusters of reports on a company when multiple reports occurred within a three-week period.3 Our final sample consisted of 4,436 recommendation changes for which all necessary data were available. Of those, 4,002 were one-level changes, 422 were two-level changes, and 12 were three-level changes.

Although actual descriptive phrases for recommendation ratings differ, sell-side stock-rating systems fall into three groups: three-, four-, and five-level systems. We used the convention that lower numbers correspond to better ratings. For example, in a three-level system, 1 is a buy, 3 is a sell, and 2 is neutral.

We measured price reactions using a multivariate regression covering 241 trading days centered on the report publication. Dummy variables were introduced to capture abnormal returns for periods around publication (see Binder 1985 and Thompson 1985). Specifically, we estimated the following regression for each observation: (Formula Omitted)

(Formula Omitted)

The coefficient delta2 in Regression 1 thus represents the abnormal daily return for the two days (0 and +1) around the report publication. For ease of interpretation, we converted the daily coefficient estimates to the equivalent cumulative abnormal return (CAR). As a result, we report a CAR of 2 times delta2 as the total abnormal return over this twoday window. Cross-sectional averages of recommendation-specific data are reported to measure sample characteristics. Regression 1 was estimated using generalized least squares, in which initial ordinary least squares residuals are used to estimate the variance-covariance matrix.

In summary, the CARs derived from Regression 1 measure share-price effects immediately before, at the time of, and immediately following publication of an analyst's recommendation change. We refer to these periods as the prepublication, release, and incorporation periods, respectively. The prepublication period captures effects that may result from prepublication release to key clients (see Lloyd-Davies and Canes 1978, and Abdel-khalik and Ajinkya 1982). The incorporation period allows for possible time delays in reaction to the publication and/or any return reversal if the market initially overreacts.

Patterns in Recommendation Changes

Table 1 presents recommendation changes segmented by the type of rating system. Changes from five-level systems constitute 41.0 percent of the sample, and four-level and three-level systems account for, respectively, 36.6 percent and 22.4 percent. Thus, more than three-fourths of recommendations come from systems that go beyond triage. For both upgrades and downgrades, about 10 percent of all observations are multilevel recommendation changes. This proportion is substantially below the almost 30 percent reported by Stickel (1995). The likely reason for the difference is that Stickel's data source rescales three- level systems into five categories. Thus, his partitioning would incorrectly identify all changes in a three-level system (about 22 percent of our sample) as multilevel changes. Our data show that such multilevel changes are relatively infrequent events.

Table 1 shows clearly that upgrades are more common than downgrades in all systems. For the sample as a whole, upgrades exceed downgrades by 37 percent. Even more striking is the ratio of upgrades to downgrades for stocks that start with a neutral rating. Table 2 partitions all single-level rating changes based on the initial and new recommendations. For instance, in a three-level system, a stock that begins with a neutral recommendation (Level 2) is more than five times as likely to be upgraded by an analyst as downgraded.
(Table Omitted)

Captioned as: Table 1.

(Table Omitted)

Captioned as: Table 2.

Another manifestation of analyst optimism is the rare use of downgrades to the worst-rating category in five-level systems. Table 2 shows only six downgrades to a 5 ("sell"), less than 1 percent of the downgrades in such systems. By comparison, in three-level systems, more than 20 percent of downgrades are to the lowest level.4 For a stock initially rated a 4, the chance of an upgrade is more than 21 times as likely as a downgrade. Data for four-category systems also show the reluctance to use negative ratings. Overall, 82.5 percent and 86.1 percent of the five- and four-level system subsamples, respectively, are changes that involve only the top three rating levels (1 through 3).

The patterns in Tables 1 and 2 reflect the practice that sell-side analysts are generally not held to a specified proportion of buys, holds, and sells. In such an environment, recommendation upgrades substantially outnumber downgrades. Furthermore, given a wider range of ratings, analysts avoid the lowest rating levels, in effect sugarcoating negative news.

Price Reactions to Single-Level Recommendation Changes

How does the market react to analysts' opinions? Table 3 provides some answers for single-level recommendation changes partitioned by the rating system and by various time periods around the recommendation publication. Three clear patterns emerge. First, prices respond to analyst recommendation changes. With the exception of the prepublication period (Days -5 to -1) for four-level systems, all the price effects across the different time intervals and rating systems are significantly different from zero. Prices move up with upgrades and down with downgrades. Moreover, price responses are not confined to the release period (Days 0 to +1) but are spread out over a wider window as markets adjust, either to prepublication revelations to some investors and/or time delays in interpreting and acting on the recommendation. These price responses indicate that analysts' research creates new and valuable information and thus corroborates prior research assessing price impacts of recommendation changes (see Bjerring, Lakonishok, and Vermaelen 1983; Dimson and Marsh 1984; Ho 1995; Stickel 1995; and Womack 1996).
Second, market responses to downgrades are typically larger than those to upgrades. Such larger effects for downgrades parallel our earlier observation that downgrades are fewer than upgrades. If analysts have a penchant to be optimistic, a rating downgrade may reflect particularly bad prospects for a company.

(Table Omitted)

Captioned as: Table 3.

Third, systems with more rating categories do not have smaller price responses for a one-level change. In fact, if anything, the price impact of a one-level change in a five-level system is larger than the effect of a

one-level change in systems with fewer categories. This finding does not support the simple explanation that more rating categories simply carve up information into small bits.

Providing further insight into the effects of rating changes, Table 4 presents cumulative abnormal returns conditioned on the initial level of the stock rating. For instance, in a three-level system, upgrades from a 2 (neutral) to a 1 (buy) see price increases of 0.57 percent in the release period. Downgrades from a 2 to a 3 (sell) experience a 1.73 percent share-price drop for the same period. For the three-level system, the patterns of price response, in part, fit straightforward predictions drawn from the portfolio actions the rating changes suggest? Specifically, an upgrade or downgrade from a 2 signals investment action (buy or sell, respectively). On the other hand, upgrades from 3 or downgrades from 1 do not convey (at least if one interprets categories literally) any need to buy or sell. As a result, one might expect price responses for changes away from a 2 rating to be more pronounced than other rating-change moves. Table 5 recasts the results to show that for three-level systems, the data are generally consistent (though not statistically significant) with these predictions once one controls for the differences between downgrades and upgrades.

Patterns in five-level systems do not track this literal interpretation of categories. Some of the largest price effects shown in Table 4 for five-level systems involve rating changes between Levels I and 2. For instance, an upgrade from 2 to 1 shows a 4.38 percent price increase (over the entire threeweek period), whereas an upgrade from 3 to 2 shows only a 2.90 percent change. One interpretation of these price patterns is that the interaction between investors and analysts involves much more subtle signaling than a literal reading of the rating categories. For some analysts, perhaps only a strong buy (1 rating) signals a "real" purchase recommendation and lower categories are reserved for more-neutral or negative opinions.

The data in Table 4 also allow examination of the effects of recommendation changes sometimes viewed as ambiguous signals. Many studies exclude analysis of changes that are not easily interpreted as either a buy or sell (e.g., downgrades from 1 to 2, or upgrades from 5 to 4 or 4 to 3). For instance, Stickel (1995) excluded downgrades from a 1 to 2 (in a five-level system) from his analysis of price effects and stated that "a revision from 1 to 2 can be interpreted as negative because of the downgrade or as positive because the buy rating of 2 indicates the analyst still believes the stock is undervalued." Table 3 shows that such changes (from 1 to 2) yield significant negative price effects in both four- and five-level systems, even if the final rating is still positive. Upgrades show a less consistent pattern. Significant price declines in downgrades from the top category, even when the resultant recommendation is positive (a 2 rating), emphasize that the information in recommendations depends on the direction of change in recommendation, not just the final recommendation level. Moreover, the patterns underscore the subtlety of communication between analysts and investors.

One intriguing attribute of the price responses in Table 4 is that a five-level system appears to convey more total information than a three-level system. For example, consider a stock that goes through all the upgrades (downgrades) from the lowest (highest) to the highest (lowest) level. Totaling the CARs for the release period over all these rating changes, we find a 2.87 percent (-6.0 percent) price movement for an upward (downward) move through a five-level system, 3.64 percent (-5.43 percent) in a four-level system, and 1.0 percent (-2.87 percent) in a three-level system. One interpretation is that finer-partitioned systems convey more information, possibly because having more rating categories provides more-precise information.

(Table Omitted)

Captioned as: Table 4

(Table Omitted)

Captioned as: Table 5.

The hypothetical cumulation exercise, however, likely overstates differences between systems for a number of reasons. Different individual analysts may deploy rating categories differently, but our sample captures only meaningful rating changes, given an analyst's practice. In this case, cumulating price effects based on averages would overstate what would actually occur if a single analyst actually took a stock through all five rating categories. Nonetheless, Table 3 shows that even a one-level change in a five-level system is accompanied by at least as large a price response as accorded a one-level change in a three-tiered system. Another caveat in interpreting our results is that differences between price reactions for the rating systems may stem from some other root cause, one that is correlated with the adoption of a particular type of system, such as the quality of the analyst research or the nature of stocks covered. Whatever the ultimate cause, price effects from four- and fivetiered systems cannot be explained by the simple hypothesis that they partition information into smaller bundles.

One additional pattern in Table 4 is that changes to extreme recommendation categories are especially informative to the market. For upgrades, changes to the highest category (1) in all systems receive the largest price responses. For downgrades, the evidence is less clear because of the rare use of some of the negative categories. Nonetheless, downgrades from the most bullish category (1) show smaller price effects than downgrades from other neutral or buy categories. Again, this finding is consistent with a subtle pattern of communication between analysts and the market. Moreover, it provides insights into why different definitions of recommendation changes have led to different empirical results in past research.6

Effects of Multilevel Recommendation Changes

As shown in Table 1, approximately 10 percent of our sample consists of multilevel recommendation changes. Of these, almost all (97 percent) are twolevel changes. One would expect such dramatic signals to convey more information than singlelevel changes. Stickel (1995) documents such a larger effect, but his data source, which forces all ratings to a five-category basis, likely misclassifies a large number of changes as multilevel when, in fact, they are single-level changes in three- or fourlevel systems.

To test for the incremental effects of multilevel changes, we estimated the following regression separately for upgrades and downgrades: (Formula Omitted)

(Formula Omitted)

The variable STRONG controls for the apparently larger price effects of recommendation changes to the extreme categories shown in earlier results. Table 6 shows that multilevel changes do have significantly larger price impacts than single-level changes. Interestingly, the coefficient estimates on MULTI are almost the same in absolute value (about 1.7 percent) for both upgrades and downgrades. This additional impact is substantial compared with the mean level of price effects for single-level changes. The incremental 1.7 percent effect is not as large, however, as the regression intercept, suggesting that the information content of a two-level change is not twice as large as for a single-level change. The coefficients on STRONG in Table 6 echo earlier conclusions. For upgrades, changes to the highest category receive the largest price responses: The coefficient estimate of 0.86 is relatively large and statistically significant. For downgrades, the

evidence is not as strong for such an "extreme recommendation" effect.7 In sum, the regression results demonstrate that multilevel recommendation changes are accompanied by larger price reactions than are single-level changes.

Conclusion

Our evidence shows that analyst recommendations convey valuable new information to markets. Rating systems designed to convey this information apparently involve subtle distinctions and communication likely motivated by revenue pressures on brokerage firms.
(Table Omitted)

Captioned as: Table 6.

Studying three-, four-, and five-category systems, we found evidence that suggests additional rating categories are used to avoid harsh statement of negative news. Such a rosy bent likely reflects unfavorable revenue effects of negative ratings. We also found that price reactions to recommendations flow from information exchange between analysts and investors involving subtle interpretations that go well beyond the actual wording of the recommendation.

We thank Bob Conroy and David McLaughlin for valuable comments.

Footnote:

Notes

Footnote:

1. We reviewed the language of rating categories for 20 major brokerage houses. Eight used five-level systems, nine used four-level systems, and the remaining three used threelevel systems. Thirty percent of the houses had systems that did not use the word "sell" but rather substituted phrases such as "underperformance" for their bottom rating.

2. For instance, Stickel (1995) used Zacks Investment Research's conversion of brokerage recommendations into a five-point scale. In the case of a three-level system, such a conversion makes all recommendation changes appear to be multilevel changes (e.g., 1 to 3 or 3 to 5) unless one specifically controls for differences in rating systems.

3. Our actual procedures used disjoint cluster analysis to identify clusters of reports. Each such cluster consists of multiple reports within an approximate three-week period and is separated from other reports by at least three weeks. See Ho (1995).

Footnote:

4. A five-level system offers four possible downgrades, whereas a three-level system offers only two. Analysts may also cease coverage rather than issue a sell recommendation.

5. We are indebted to David McLaughlin for bringing this idea to our attention.

6. For instance, Womack used changes only to extreme categories and found larger price effects of analyst recommendation changes than have many other studies. Stickel (1995) found an increased price response for changes to extreme categories.

7. In this regard, our conclusions differ from those of Stickel (1995), who reported (Table 6) smaller effects of extreme recommendations in buy versus sell recommendations. As noted earlier, however, his data do not

distinguish between rating systems adequately. In addition, he focuses on buy and sell recommendations and leaves out downgrades, such as from a 1 to a 2 rating.

Reference:

References

Reference:

Abdel-khalik, A., and B. Ajinkya. 1982. "Returns to Informational Advantages: The Case of Analysts' Forecast Revisions." Accounting Review, vol. 57, no. 4 (October):661-80. Binder, J.J. 1985. "On the Use of the Multivariate Regression Model in Event Studies." Journal of Accounting Research, vol. 23, no. 1 (Spring):370-83.

Bjerring, J.H., J. Lakonishok, and T. Vermaelen. 1983. "Stock Prices and Financial Analysts' Recommendations." Journal of Finance, vol. 38, no. 1 (March):187-204.

Reference:

Dimson, E., and P. Marsh. 1984. "An Analysis of Brokers' and Analysts' Unpublished Forecasts of U.K. Stock Returns." Journal of Finance, vol. 39, no. 5 (December):1257-92. Ho, Michael J. 1995. Analyst Recommendation Changes and the Dynamics of the Market Response. Unpublished doctoral thesis, Darden School of Business, University of Virginia. Hulbert, Mark. 1993. The Hulbert Guide to Financial Newsletters, 5th ed. New York: Dearborn Financial Publishing, Inc.

Reference:

Lloyd-Davies, P., and M. Canes. 1978. "Stock Prices and the Publication of Second-Hand Information." Journal of Business, vol. 51, no. 1 (January):43-56.

Siconolfi, Michael. 1995. "Many Companies Press Analysts to Steer Clear of Negative Ratings." Wall Street Journal (July 19):A1. Stickel, S.E. 1985. "The Effect of Value Line Investment Survey Rank Changes on Common Stock Prices." Journal of Financial Economics, vol. 14, no. 1 (March):121-43. .1995. "The Anatomy of the Performance of Buy and Sell

Reference:

Recommendations." Financial Analysts Journal, vol. 51, no. 5 (September/October):25-39.

Thompson, R. 1985. "Conditioning the Return-Generating Process on Firm-Specific Events: A Discussion of Event Study Methods." Journal of Financial and Quantitative Analysis, vol. 20, no. 2 (June):151-68.

Womack, K.L. 1996. "Do Brokerage Analysts' Recommendations Have Investment Value?" Journal of Finance, vol. 51, no. I (March):137-67.

Author Affiliation:
Michael J. Ho is an assistant professor of finance and the Dr. Udane Tejapaibul Family Term Chair at Babson College. Robert S. Harris is the C. Stewart Sheppard Professor of Business Administration in the Darden School of Business at the University of Virginia.

GEOGRAPHIC NAMES: US

DESCRIPTORS: Studies; Stock brokers; Investment policy; Ratings & rankings;

Stock prices; Valuation; Impact analysis
CLASSIFICATION CODES: 9190 (CN=United States); 9130 (CN=Experimental/Theoretical); 8130 (CN=Investment Services); 3400 (CN=Investment analysis)

00511492 90-37249
Composite Analyst Earnings Forecasts: The Next Generation
Brown, Lawrence D.; Chen, David M.
Journal of Business Forecasting v9n2 PP: 11-15 Summer 1990 ISSN: 0278-6087 JRNL CODE: JBT
DOC TYPE: Journal article LANGUAGE: English LENGTH: 5 Pages
SPECIAL FEATURE: References

ABSTRACT: The simple consensus forecast (SCF), the most commonly used measure of earnings expectations, is easy to understand and simple to calculate, and it has a superior predictive ability relative to time-series forecasts. However, some disadvantages are that it: 1. gives equal weight to all **analysts**, regardless of their **comparative** track records in predicting earnings, 2. is outperformed by the most recent individual earnings forecasts, and 3. does not update the individual **analyst** forecasts after quarterly earnings announcements. A sophisticated **analyst** -based model, the weighted consensus forecast (WCF), is proposed. The WCF updates **analysts** ' forecasts for the quarterly earnings announcements and gives higher weights to more recent forecasts and to **analysts** with better track records. The predictive accuracy of the 2 measures is **compared** using data on 1,476 firms representing 85 industries. For all firm/time observations, the WCF is more accurate than the SCF 66.44% of the time. The proposed measure provides more accurate forecasts for all 85 industry categories.

01176688 98-26083
The best and the worst: **Bloomberg**'s second annual analysts **survey**, and the top analysts top picks.
LaMonica, Paul R
Financial World v165n2 PP: 38-42 Jan 30, 1996 CODEN: FIWOAR ISSN: 0015-2064 JRNL CODE: TWO
DOC TYPE: Journal article LANGUAGE: English LENGTH: 4 Pages
SPECIAL FEATURE: Charts
WORD COUNT: 1970

ABSTRACT: **Bloomberg**'s second annual **survey** of analysts' stock picks for 1995 is presented. The number one performer was Scott Sacane, who covers biotechnology for Furman Selz. His five recommendations were up an average 245% for the period between July 1, 1994 and September 29, 1995. Because the market as a whole did so well, only 16 of 605 analysts in the **survey** posted losses this year, versus 222 in last year's **survey** of 633 analysts. The medium gain for the 605 analysts was about 34%, slightly less than the 35.5% gain for the S&P 500. Several of the top analysts said picking under-followed companies is key to their selection process. Although it was hard to lose money in a bull market, 16 analysts were down for the **survey** period.
TEXT: Where was the best place to make money in 1995? For most of the year, high tech.

So it's not surprising that of the 25 brokerage analysts whose recommendations performed the best in **Bloomberg**'s second annual **survey** of analysts' stock picks, 23 cover high-tech stocks. The No. 1 performer was Scott Sacane, who covers biotechnology for Furman Selz. His five recommendations were up an average 245% for the period between July 1, 1994 and Sept. 29, 1995.

Because the markets as a whole did so well, only 16 of the 605 analysts in the **survey** posted losses this year, versus 222 in last year's **survey** of 633 analysts (which FINANCIAL WORLD dubbed the Lemon List because it only reported on the worst performers). This year's 25 worst stock pickers follow a mixed bag of industries ranging from retailing to steel to energy. Three of the 25 worst performers were gaming analysts, including the worst, Amy de Rham of Montgomery Securities. A fourth--David Anders--covers gaming technology stocks.

The median gain for the 605 analysts was about 34%, slightly less than the 35.5% gain for the S&P 500. Only 227 analysts, 38% of those in the **survey**, beat the market. (For details of **Bloomberg**'s **survey** methodology, see box, page 42.)

Fortunately for technology analysts, the sector's run pretty much coincided with the time frame of the **survey**. The Morgan Stanley High-Tech index of 35 stocks was up 110% during the **survey** period, while the Philadelphia Semiconductor index had a mind-boggling total return (price gain plus reinvested dividends) of 290%. What did they say about not mistaking brains for a bull market?

This wasn't the case with Sacane, the biotech **analyst** with the top **ranking**. A molecular biologist by training, he made only five recommendations during the period of the **survey**, but each paid off. His secret: Before he even looks at a company's financials, Sacane

researches the main drugs the company is developing, the diseases they are intended to treat and the likelihood that the drugs will get Food and Drug Administration approval and then generate revenues. That's especially important since the stocks of many of the newer biotech companies initially move more on news about a drug's test results than on a company's earnings or sales expectations, Sacane notes.

Look at Cephalon, which Sacane recommended in early June 1995. It increased over 130% by the end of the **survey** period. Why? Sacane's buy recommendation on Cephalon happened to come just 10 days before the company announced that Myotrophin, the drug it is developing to treat amyotrophic lateral sclerosis, more commonly known as Lou Gehrig's disease, had promising test results with humans. The stock leaped 75% in one day on the news.

Sacane still likes Cephalon. He is confident that Myotrophin will receive FDA approval sometime in late 1996 and enter the market shortly afterward.

Sacane's other big hits last year were Gilead Sciences and Neurogen. Gilead doubled during the **survey** period and Neurogen was up over 340% since September 1994.

Another top-performing nontechnology **analyst**, Prudential's Jennifer Scutti, **ranked** 23rd by recommending relatively mundane financial services companies. Both of her big hits were touted in September 1994: Aames Financial, a home mortgage lender, and Oxford Resources, which leases automobiles to people and businesses.

Scutti placed a buy on Aames when the stock was at 8 3/8, changed to a hold when it ran up to 13 1/4 by the following March and then reissued a buy after the stock fell back to 12. By the end of the **survey** period Aames had more than doubled, to 29 1/4. Oxford nearly doubled by the end of the period, thanks to strong earnings growth.

Scutti says Aames and Oxford have great growth potential but were trading at lower multiples than she felt was warranted. She also picked the companies when few analysts were tracking them.

In fact, several of the top analysts say picking under-followed companies is a key to their selection process. "If you have 50 people that follow a company, how do you differentiate yourself," says Betty Lyter of Montgomery Securities, this year's second best **analyst**. Adds Jonathan Cohen, **ranked** 20th, who covers special situations for Smith Barney: "Hopefully, I can learn more than other people and exploit that."

Given technology's torrid run, it's little surprise that Hambrecht & Quist, a firm that specializes in technology companies, finished tops among all brokerages. This year we **rank** the firms by what we call the outperformance ratio, the percentage of the firm's analysts who beat the S&P 500. Seven of H&Q's nine analysts in the **survey** beat the S&P 500, giving the firm an outperformance ratio of 78%. The firm's analysts posted an average gain of 74%.
H&Q is followed by Cowen and Gruntal. Both firms had an average gain of a little under 60% and both could boast that at least 70% of their analysts beating the S&P. On the other hand, A.G. Edwards, Merrill Lynch, Wheat First Butcher Singer and Goldman, Sachs were the worst-performing firms in the **survey** in terms of the number of analysts beating the S&P. Collectively, A.G Edwards's 31 analysts underperformed the S&P and only six of them individually beat the S&P 500. Only about a third of the analysts at Merrill, Wheat First and Goldman outperformed the market.

What about this year's lemons, the worst 25 analysts? True, it was hard to lose money in this bull market. Still, 16 analysts were down for the **survey** period. The two worst, de Rham and Jeffrey Omohundro, a restaurant **analyst** at Wheat First, each made five picks, all toward

the end of the **survey**'s time frame. And just as the **survey** rewarded large gains over short periods of time, it penalized large losses over short periods.

Of de Rham's five picks, her four buys were losses, including Casino America, down 36% and Ameristar Casinos, down 19%. And the price of the only stock she had a hold on, Grand Casinos, increased 50% between the time she put a hold on it and the end of the **survey**. Since a hold is treated as an investment in the S&P 500, de Rham only got credited with the S&P's 14% increase during that period, not Grand Casinos' 50% increase. Ouch.

Only two of last year's lemons--Kevin Tang of Alex. Brown & Sons and Oppenheimer's Douglas Augenthaler--are on this year's shorter version of the Worst List. Tang, whose picks were down 7%, is the only **analyst** to average a loss during both surveys. The biotechnology **analyst** lost big with his buy recommendation on PerSeptive Technology II, a company that Alex. Brown underwrote when it went public in 1993. Its price sank more than 50% by the end of the **survey** period.

Tang also had a buy on Aramed, which fell 32%. Why? Aramed was founded specifically to develop drugs based on the technology of Gensia, a company which Tang had a hold on at the beginning of the **survey** when the stock was at 9 1/4. Tang then changed his recommendation to a buy after Gensia said that it had halted testing of its lead drug, Protara, in mid-August 1994. The stock rose as high as 12 1/4 following his rating change when Tang wrote in a research report that he thought the reason Gensia stopped trials on Protara was because it must have already proven to provide some benefits. He was dead wrong. Two months later, the stock plummeted after Gensia announced that Protara had failed in human testing. Still, Tang kept the buy on the stock and it ended the **survey** period at 5 1/2, down 50%. And as Gensia sank, so did Aramed. Gensia wound up purchasing Aramed in June.

The other Lemon List repeater, Augenthaler, is an environmental sciences **analyst** with Oppenheimer who admits that many of his picks have not panned out. He had a buy on EcoScience throughout the **survey** period, but it lost over 70% as the company never seemed to meet the earnings expectations of the few analysts who covered it. But Augenthaler argues the **survey** isn't an accurate assessment of performance because of the arbitrary time frame.

How did last year's other lemons do? Telecommunications equipment **analyst** Therese Murphy, last year's No. 1 lemon, can't be found on any list because she was the 26th worst performer.

And one **analyst** on last year's Lemon List is no longer in equity research. Last year's third worst, Bear Stearns research director Mark **Kurland**, was listed as a paper and forest products **analyst**. But in this year's **survey**, Linda Lieberman, Bear's other paper and forest products **analyst**, had an average gain of 46%.

All in all, eight of last year's bottom 25 underperformed the market this year. Still, several of the analysts on last year's Lemon List fared much better this year. Alex. Brown's Steve Eskenazi, who follows new media technology and **ranked** 54 on last year's Lemon List, finished 16th best overall this year. Morgan Stanley technology **analyst** Robert Maire, 56th on last year's Lemon List, **ranked** 25th on this year's best list. And two other technology analysts, Goldman, Sachs's Greg Gould, last year's fifth worst, and Richard Sherlund, last year's 21st worst, both beat the market this year, each of them showing gains of about 70%.

But if many of the technology stocks continue their current retreat, look for another shakeup of the two lists next year.

How the **Survey** Was Conducted

Bloomberg tracked 1[redacted]18 stock recommendations made [redacted]605 analysts from 20 firms between July 1, 1994 and June 30, 1995. Recommendations are broken down into only three categories: buy, hold and sell. An outperform, for example, is considered a buy, while a neutral is treated as a hold. Recommendations were tracked for as long as they were in place. Those that remained in place on June 30, 1995 were monitored through Sept. 29, 1995.

There have been some notable changes in this year's methodology. Last year, **Bloomberg** treated a downgrade to hold as a recommendation to sell the stock short. This year, a hold was treated as an investment in the S&P 500 index.

Also, this year the length of time a recommendation was in place was a factor. **Bloomberg** used a formula that rewards an **analyst** who had a buy on a stock that had a return of 50% over one month more than an **analyst** who earned a 50% return over five months, for example.

Last year, an **analyst** only needed to make three recommendations to be included in the **survey**. This year, at least five were required.

And finally, last year, **Bloomberg** only tracked new recommendations made during the designated time frame. For this **survey**, recommendations already in place at the beginning of the **survey** were included, though **Bloomberg** began tracking the stock's price when the **survey** period started. This was the most significant change in the **survey**'s methodology because it drastically increased the number of recommendations that were tracked. More important, it helped to provide a more accurate picture of an **analyst**'s performance.

For example, Betty Lyter of Montgomery Securities, the second-best **analyst** in this year's **survey**, with a gain of almost 215%, wouldn't have been so high on the list if last year's methodology was used. That's because she had buy recommendations in place on Macromedia and Softkey at the beginning of the **survey**. She never changed her picks, and by the end of the **survey** period, Macromedia's price had increased more than 550% while Softkey's leaped over 250%. Last year these picks wouldn't have been included.

One caveat: Not all firms are represented. Among the missing: PaineWebber, J.P. Morgan and Donaldson, Lufkin & Jenrette. **Bloomberg** contacted many brokerages about the **survey** and asked research directors to verify the data. If the research director would not verify the data, that firm was not included in the **survey**.

GEOGRAPHIC NAMES: US

DESCRIPTORS: Ratings & **rankings**; Investment advisors; Polls & surveys ; Investment policy; Manypeople; Manyindustries; Manycompanies; Statistical data
CLASSIFICATION CODES: 9190 (CN=United States); 8130 (CN=Investment services); 3400 (CN=Investment analysis); 9140 (CN=Statistical data)

18/9/2

00984880 96-34273
The lemon list
Taub, Stephen; Sklar, Jeff
Financial World v164n6 PP: 28-34 Feb 28, 1995 CODEN: FIWOAR ISSN: 0015-2064 JRNL CODE: TWO